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RESEARCH ARTICLE

A Speed-Invariant Template-Based Approach for Estimating Running Temporal Parameters Using Inertial Sensors

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ABSTRACT Segmentation of running data into gait cycles and stance/swing phases is crucial for evaluating running biomechanics. The benefit of magneto-inertial sensors is their ability to capture data in outdoor conditions. However, state-of-the-art inertial-based methods for estimating running temporal parameters are limited to a restricted range of running speeds and, thus, not able to analyze running at variable speeds. This limitation prevents their use for real-world analysis for a wide range of runners and for sports disciplines where athletes vary their running speed. This study evaluated the speed-dependance of eight relevant foot-mounted inertial-based methods from previous research and proposed a novel method that could be robust to speed changes. The proposed method applied, for the first time, a template-matching algorithm based on dynamic time warping to running analysis and compared it to existing methods. All the implemented methods were tested on 30 runners at different speeds ranging from jogging to sprinting (8 km/h, 10 km/h, 14 km/h, 19-30 km/h) on both treadmill and overground. The most speed-robust performance was achieved by the proposed template-based method, providing estimation errors below 0.1% in stride, between 7%-19% in stance, and between 3%-6% in swing across running speeds. Conversely, all the tested methods from the literature were significantly speed-dependent. Thus, this study suggested that template-based approach is a valid solution for the inertial-based estimation of temporal parameters during running from slow jogging to fast sprinting. MATLAB codes and templates have been made available online.

INDEX TERMS Contact time, inertial measurement unit (IMU), running, sprinting, temporal parameters, wearable sensors.

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I. INTRODUCTION

Running is an increasingly popular leisure and competitive activity worldwide. Assessment of running biomechanics plays a crucial role in reducing running-related musculoskeletal injuries and in developing appropriate training and/or rehabilitation programs [1]. The use of wearable inertial measurement units (IMUs) allows for examination of running biomechanics in various environments and populations, including field-based sports. Based on the accelerations and angular velocities of the body segments where IMUs are attached, it is possible to estimate running temporal, kinematic, and kinetic parameters [2]. Since running is a cyclical activity, the identification of running gait events, namely initial contact (IC) and final contact (FC) instants, is necessary to segment continuous running data into gait cycles to provide reliable and commonly reported biomechanical or performance descriptors [3].

Several methods of detecting IC and FC events have been proposed using various IMU placement (e.g., pelvis [4], shanks [5], and feet [6]). Foot placement has demonstrated the greatest accuracy for estimating inertial-based spatio-temporal parameters [7], [8], [9], [10].

Foot-mounted inertial-based methods for estimating IC typically use: *i*) peak detection either on accelerometric signals (acceleration norm [11], [12], [13], [14], anteroposterior acceleration [15]) or mediolateral angular velocity [6]; or *ii*) machine learning [16], [17]. Methods for estimating FC typically use: *i*) peak detection either on accelerometric signals (anteroposterior acceleration [15], vertical acceleration [11], [14], [18]) or angular velocity (mediolateral angular velocity [6] or angular velocity norm [13]; *ii*) thresholding on acceleration norm [12]; or *iii*) machine learning [16], [17].

These methods have important and different limitations to consider. Namely, peak detection and thresholding require fine-tuning of their parameters according to specific running characteristic,s such as running speed, while machine learning methods lack generalizability outside of the dataset (subject characteristics) from which they were trained [19]. Hence, most state-of-the-art methods have been tested and validated only for specific running speed ranges: low running speed (8-12 km/h) [15], [16], [18], moderate running speed (13-16 km/h) [11], [12], and fast running speed (>16 km/h) [13], [20]. Importantly, running speed influences running biomechanics [21], including foot strike patterns [22]. These differences in biomechanics as a result of running speed can be seen in both inertial signal intensity and morphology as well as changes in contact time with respect to running gait cycle (Fig. 1). Recent studies have demonstrated that inertial-based IC and FC estimation has reduced accuracy at running speeds outside of the range on which it was specifically designed [6], [22]. This limitation reduces the applicability of the existing methods to analyze running across a wide range of speeds (runners) and in scenarios where running speeds are not constant or frequently change (e.g., soccer, baseball, etc.).

A promising mathematical solution to overcome the aforementioned limitation is the dynamic time warping (DTW) algorithm. The DTW was originally conceived to analyze and compare temporal sequences, non-linearly distorting them, through stretching signal morphology, to find corresponding time events [23].

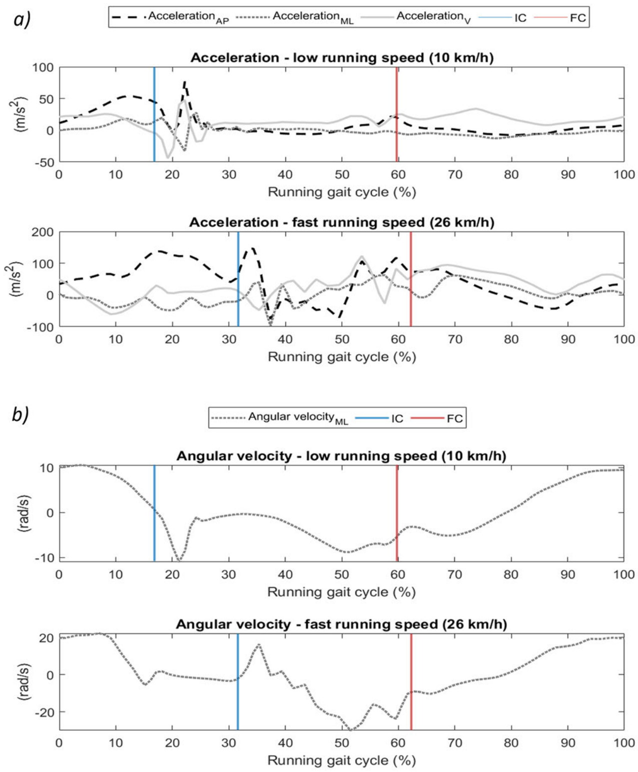

FIGURE 1. Representative data of acceleration (a) along anteroposterior (AP), mediolateral (ML), and vertical (V) axis, and angular velocity (b) along ML axis at different running speeds (10 km/h and 26 km/h). Abscissa values are the normalized running gait cycle between two consecutive mid-swing instants (corresponding to 0% and 100%). The running gait cycles lasted 0.770 s and 0.490 s at 10 km/h and 26 km/h, respectively. Vertical lines represent the initial contact (IC) in blue and final contact (FC) in red. Ordinate ranges are intentionally different to illustrate the morphological differences of the inertial data across running speeds.

Recently, DTW was applied to motion analysis for activity classification [24], [25], [26], symmetry quantification [27], and template-based gait cycle segmentation [28], [29], [30], [31], [32]. Specifically, it was shown that methods incorporating the DTW algorithm can be used for stride segmentation during walking in healthy and pathological cohorts [29], [30], but there is no evidence on their applicability on running analysis.

In this study, we propose a novel template-matching algorithm based on DTW for running analysis to address the gap in methodology regarding inertial-based methods that could estimate gait cycle parameters at any speed. The performance of the proposed DTW template-based method is expected to be superior to existing methods that were mostly conceived for specific running speeds and based on speed-dependent signal morphology, possibly limiting their generalizability to different speeds [11], [12], [13], [15], [18], [20].

To accomplish this primary goal, we addressed the following specific aims:

1) to assess and compare the sensitivity to speed changes of eight state-of-the-art inertial-based methods for the estimation of running temporal parameters based on peak detection and/or thresholding [5], [6], [11], [12], [13], [15], [18], [20];
2) to assess the validity and the sensitivity to speed changes of a novel DTW template-based method for running temporal parameters expected to be robust to running speed variations.

Methods were evaluated on both treadmill and overground running at different speeds (8 km/h to 30 km/h) using optical motion capture system or pressure insoles as reference, respectively for indoor and outdoor conditions.

II. MATERIALS AND METHODS

This section details the implementation and the procedure for assessing the performances of nine inertial-based methods for the estimation of running temporal parameters (eight state-of-the-art methods and a novel DTW template-based method). The content is organized as follows:

A. Existing methods selected for comparison;
B. Description of the DTW template-based method:
   1) Theoretical background on DWT algorithm;
   2) Workflow of the DTW template-based method;
   3) Templates definition;
   4) Data pre-segmentation;
   5) Identification of initial and final contacts via template matching.
C. Experimental data collection:
   1) Slow running speed dataset (8 km/h and 10 km/h);
   2) Moderate running speed dataset (14 km/h);
   3) Fast running speed dataset (19-30 km/h);
   4) Description of the running datasets.
D. Methodology for performance assessment:
   1) Validation of DTW template-based method;
   2) Comparative assessment and statistical analysis.

A. EXISTING METHODS SELECTED FOR COMPARISON

Eight different methods for the identification of running events were selected from the literature based on their replicability and were implemented (Table 1) [5], [6], [11], [12], [13], [15], [18], [20]. The selected methods primarily relied on peak detection and thresholding techniques using shoe-mounted IMU data, except for M6 and M8, which were originally designed for shank-mounted IMUs and subsequently adapted for shoe-mounted applications. M1 and M2 had been previously tested on slow running speeds, M3 and M4 on moderate running speeds, M5 and M6 on a wider speed range (from slow to fast speeds), and M7 and M8 on fast speeds.

No machine learning methods were included in this comparative analysis due to their dependence on dataset size and because no models trained on a wide range of running speeds were available.

Once the initial and final contact were identified with each method, a stride was defined by two consecutive initial contacts with the ground of the same foot. Within a stride, stance duration was the time interval between an IC and the consecutive FC instant, and the swing duration was the time interval between an FC and the consecutive IC instant.

B. DESCRIPTION OF THE DTW TEMPLATE-BASED METHOD

1) THEORETICAL BACKGROUND ON DTW ALGORITHM

The DTW algorithm distorts, by stretching, two time series with different morphologies so that their time vectors match, allowing to compare them (Fig. 2). Time samples of the two time series are paired by minimizing the cumulative Euclidean distance between the series, preserving the first and last samples of both time series.

For *signal x* with size Nx1 and *signal y* with size Mx1, the cost matrix $\boldsymbol{C}$ [NxM] is computed:

$$\boldsymbol{C} = \begin{bmatrix} d_{x_1y_1} & \dots & d_{x_1y_M} \\ \vdots & \ddots & \vdots \\ d_{x_Ny_1} & \dots & d_{x_Ny_M} \end{bmatrix} \tag{1}$$

where $d_{x_iy_j}$ is the Euclidean distance between the *i-th* sample of *signal x* and the *j-th* sample of *signal y*. For monodimensional signals, $d_{x_iy_j}$ is:

$$d_{x_iy_j} = \sqrt{(x_i - y_j)^2} \tag{2}$$

The accumulated cost matrix $\boldsymbol{A}$ [NxM] contains the information of the cumulative distance between *signal x* and *signal y*. The first row of matrix $\boldsymbol{A}$ is filled with the cumulative sum of the distances between the first sample of *signal x* and all the samples of *signal y*:

$$\boldsymbol{A}(1, j) = \sum\nolimits_{n=1}^{j} \boldsymbol{C}(1, n) \text{ with } j = 1, \dots, \mathrm{M} \tag{3}$$

The first column of matrix $\boldsymbol{A}$ is filled with the cumulative distance between the first sample of signal y and all the samples of *signal x*:

$$\boldsymbol{A}(i, 1) = \sum\nolimits_{n=1}^{i} \boldsymbol{C}(n, 1) \text{ with } i = 1, \dots, \mathrm{N} \tag{4}$$

Then all the other values of matrix $\boldsymbol{A}$ are filled as follows:

$$\boldsymbol{A}(i, j) = \boldsymbol{C}(i, j) + min\{\boldsymbol{A}(i-1, j-1); \boldsymbol{A}(i-1, j); \boldsymbol{A}(i, j-1)\} \tag{5}$$

where a generic value of matrix $\boldsymbol{A}$, $\boldsymbol{A}(i,j)$, indicates the total cumulative distance between *signal x* and *signal y* associated with their respective *i*-th and *j*-th time samples.

The final cumulative Euclidean distance d_{DTW} quantifies the similarity between *signal x* and *signal y* and it is equal to the "last" value of matrix $\boldsymbol{A}$:

$$d_{DTW} = \boldsymbol{A}(N, M) \tag{6}$$

To provide the best alignment between the two "warped" signals with respect to a new common time axis, an Optimal

TABLE 1. Implemented state-of-the-art methods for the estimation of initial and final contact instants during running.

Method	Reference	IMU positioning	Running speed	Initial contact definition	Final contact definition
M1	Chew et al., 2018	Foot dorsum	8-11 km/h	Minimum in anteroposterior acceleration	Minimum in anteroposterior acceleration after the initial contact
M2	Bailey and Harle, 2015	Rearfoot lateral side	8.2-12.2 km/h	Beginning of the descent slope of first derivative of mediolateral angular rate	Local maximum in vertical acceleration
M3	Benson et al., 2019	Foot dorsum	9.7-13.0 km/h	Peak in acceleration norm	Major peak in vertical acceleration
M4	Mo and Chow, 2018	Foot dorsum	11.2-14.8 km/h	Peak in acceleration norm	Crossing a threshold in acceleration norm
M5	Falbriard et al., 2018	Foot dorsum	8-20 km/h	Minimum in mediolateral angular rate in the first half of mid-swing to mid-swing cycle	Minimum in mediolateral angular rate in the second half of mid-swing to mid-swing cycle
M6	Yang et al., 2022	Distal mediolateral tibia	Slow to fast running	Peak in acceleration norm	Maximum in mediolateral angular rate
M7	Blauberger et al., 2021	Rearfoot lateral side	Sprinting	Minimum in acceleration norm	Minimum between two peaks in angular rate norm
M8	Schmidt et al., 2016	Distal mediolateral tibia	Sprinting	Crossing a threshold in vertical acceleration, with a continuous slope of mediolateral angular rate	Minimum in vertical acceleration

Warping Path (OWP) is selected to associate the samples of *signal x* to the samples of *signal y*. Using a backward approach, OWP(end) is initialized to the associated samples (x_N, y_M). Each point of OWP is updated with associated samples (x_i, y_j), up to reach OWP(1) that must be equal to the associated samples (x_1, y_1), moving up, moving left, or moving up-left in matrix $\boldsymbol{A}$ to minimize the cumulative distance. For instance, OWP(end-1) contains the pair of x-y samples among (x_{N-1}, y_M), (x_{N-1}, y_{M-1}), or (x_N, y_{M-1}) providing the lowest value of $\boldsymbol{A}$. Fig. 2*c* graphically shows matrix $\boldsymbol{A}$ highlighting OWP.

The result of the DTW is the alignment of the *signal x* and *signal y* so that corresponding morphological features of the two "warped" time series appear at the same location on the shared time axis, maximizing the similarities between them (Fig. 2*b*).

2) WORKFLOW OF THE DTW TEMPLATE-BASED METHOD

The proposed DTW template-based method (TB_{DTW}) was based on matching templates (i.e., running gait cycles annotated with IC and FC instants) and a generic running gait cycle through the DTW algorithm. To this purpose, the following steps were implemented: *i*) definition of the most representative templates for different running speeds; *ii*) pre-segmentation of the running trials into mid-swing to mid-swing running gait cycles; *iii*) template-matching based on DTW between the generic running gait cycle under analysis and the templates; and *iv*) estimation of running temporal parameters (Fig. 3).

3) TEMPLATES DEFINITION

Acceleration norm and mediolateral angular velocity were used to identify IC and FC instants, respectively, based on preliminary heuristic observations of signal morphology. In addition, to take into account that variation in the running speed can affect both inertial signals morphology and the percentages of the running gait cycle where IC and FC occur, we adopted six different templates depending on running events to detect (IC or FC) and running speed range (S: slow, M: moderate; F: fast): $\mathbf{T}_{S-IC}$, $\mathbf{T}_{M-IC}$, $\mathbf{T}_{F-IC}$ and $\mathbf{T}_{S-FC}$, $\mathbf{T}_{M-FC}$, $\mathbf{T}_{F-FC}$. Each template was defined between consecutive mid-swing instants of the same foot (Fig. 4).

The abovementioned templates were defined using three different running datasets collected at different speed ranges (see paragraph "Experimental data collection"). For instance, the "slow speed acceleration norm template" ($\mathbf{T}_{S-IC}$) was extracted from the running gait cycle characterized by the minimum value of the averaged DTW-based cumulative Euclidean distance between the acceleration norm curves computed over all possible running gait cycles combinations of the "slow running speed dataset" [29]. The same procedure was followed for the selection of all the remaining templates.

Each template was annotated with reference running events (IC or FC) extracted using a gold standard (GS) method (Appendix).

The procedure for the definition of the templates, including annotation, is required to be performed only once (Fig. 3*a*).

The six templates are available at https://github.com/H-MOVE-LAB/run_imu.git.

4) DATA PRE-SEGMENTATION

To maximize stride detection accuracy, running trials were segmented in running gait cycles, which were identified by two consecutive mid-swing instants assumed to coincide with the instants of maximal mediolateral angular velocity [33].

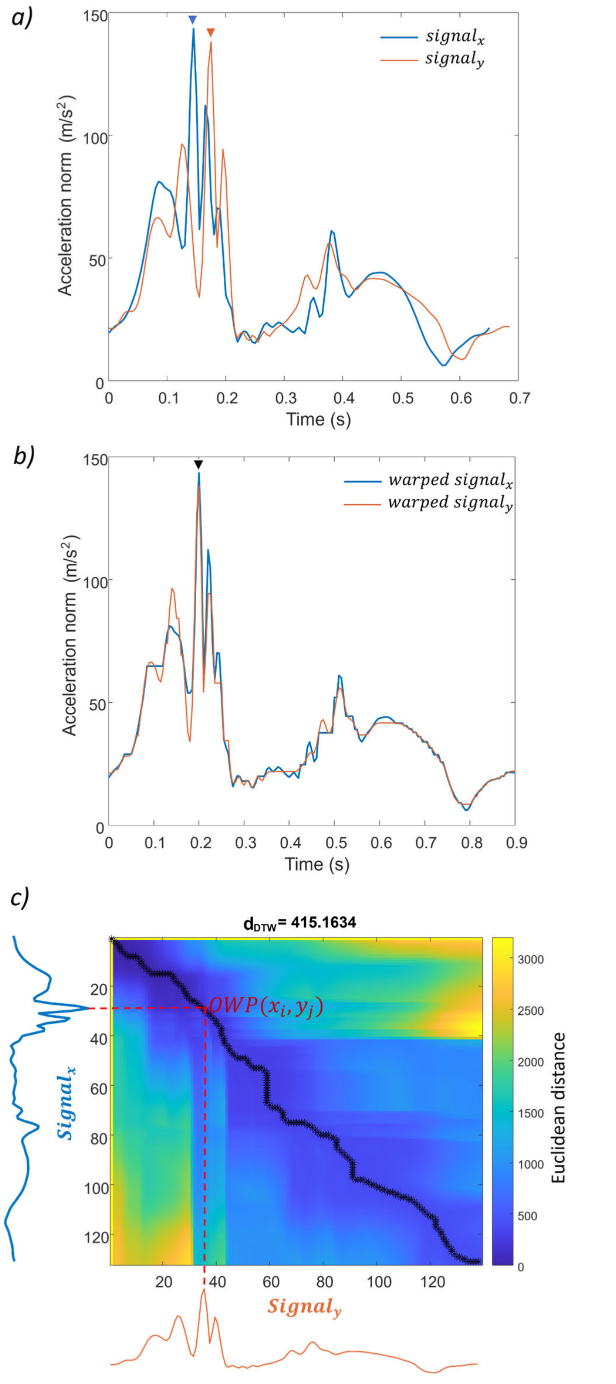

FIGURE 2. **Example of two patterns of acceleration norm (thicker signal *x* in blue and signal *y* in orange), before (Fig. 2*a*) and after the dynamic time warping technique (Fig. 2*b*). Triangles highlight the prominent peak of signal *x* (in blue) and signal *y* (in orange) (Fig. 2*a*). Dynamic time warping aligns in time morphologically corresponding points (e.g., triangles in Fig. 2*a* and Fig. 2*b*). Fig. 2*c*: Graphical representation of matrix A of accumulated costs. The color code shows lower sample-to-sample distances in blue and higher ones in yellow. The black path in the matrix represents the optimal warping path OWP, which minimizes the cumulative distance between the two signals. $OWP\left(x_i, y_j\right)$ is a generic point of the warping path containing the associated sample x_i of signal x and sample y_j of signal y.**

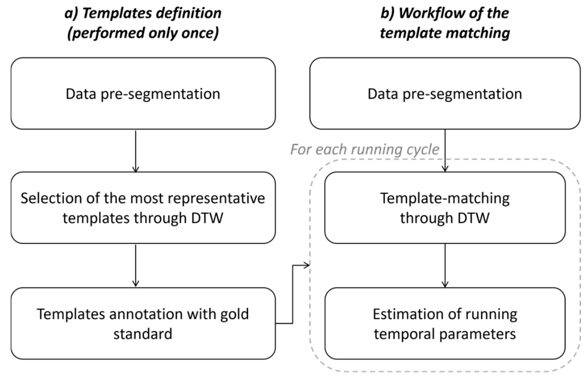

FIGURE 3. **Workflow of *a*) the template definition and *b*) the proposed method based on template-matching (TB_{DTW}). The templates definition is performed once and then the selected templates are used to estimate the running temporal parameters of novel datasets to analyze.**

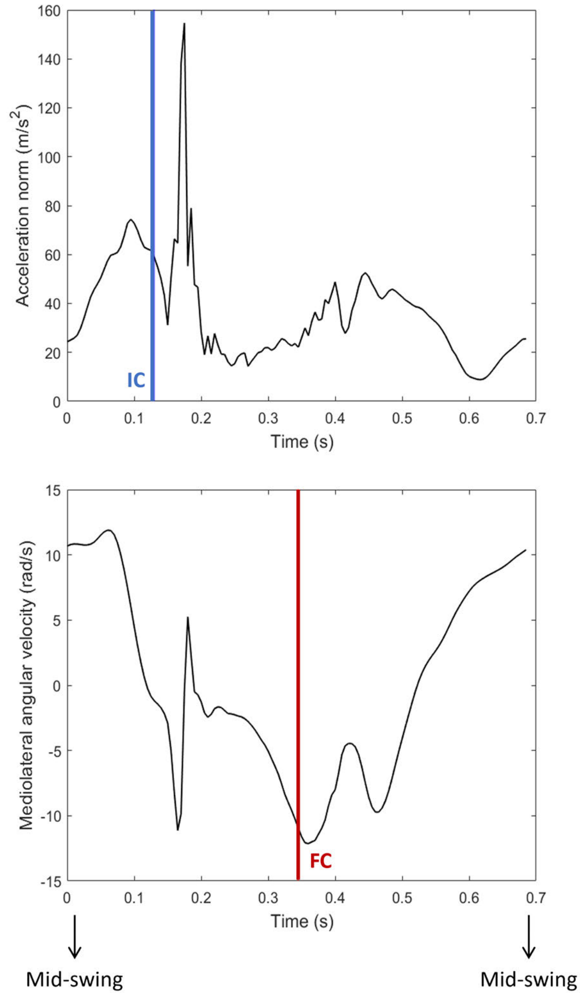

FIGURE 4. **Templates at moderate running speed (14 km/h). From above: the acceleration norm and the mediolateral angular rate segmented between consecutive mid-swing instants. IC = initial contact (blue vertical line); FC = final contact (red vertical line). The complete template library is available at https://github.com/H-MOVE-LAB/run_imu.git.**

To improve the identification of mid-swing peaks, the angular velocity was filtered with a second-order Butterworth filter using a speed-specific cut-off frequency. This cut-off frequency was determined using an automatic procedure based on the average stride frequency of the test under analysis [6]. Specifically, the cut-off frequency was set equal to the average stride frequency increased by 50% (values between 2 and 3 Hz).

5) IDENTIFICATION OF INITIAL AND FINAL CONTACTS VIA TEMPLATE-MATCHING

A DTW template-based comparison was performed for the identification of IC and FC events for each segmented running gait cycle analyzed.

As in general the running speed of each running gait cycle is not known a priori, we tested all speed-specific templates to identify the "most similar" one with respect to the specific running gait cycle under analysis.

The procedure for identifying running events is described in detail with reference to IC of a generic *k-th* running gait cycle. A cumulative Euclidean distance d_{DTW} was calculated between the generic *k-th* cycle and $\mathbf{T}_{\mathrm{S-IC}}$, $\mathbf{T}_{\mathrm{M-IC}}$, $\mathbf{T}_{\mathrm{F-IC}}$ templates. The template corresponding to the lowest d_{DTW} was selected as the "most similar template" for the generic *k-th* cycle ($\mathbf{T}_{\mathrm{ICk}}$). The template-matching procedure then allowed to derive the IC of the *k-th* cycle based on the position of the reference IC of $\mathbf{T}_{\mathrm{ICk}}$ by exploiting the optimal warping path $\mathrm{OWP_k}$ as explained below. Let i^* be the sample of $\mathbf{T}_{\mathrm{ICk}}$ in correspondence of the IC event. Based on $\mathrm{OWP_k}$ resulting from the DTW-based alignment (Fig. 2), the sample j^*,corresponding to the IC position on the *k-th* cycle, was identified.

The procedure for identifying FC was similar using $\mathbf{T}_{\mathrm{S-FC}}$, $\mathbf{T}_{\mathrm{M-FC}}$, $\mathbf{T}_{\mathrm{F-FC}}$.

The running temporal parameters (i.e., stride, stance, and swing durations) were computed after the IC and FC events were estimated for each *k-th* cycle.

C. EXPERIMENTAL DATA COLLECTION

Three different datasets were collected enrolling a total of 30 recreational and elite runners to create a heterogeneous database. The study protocol followed the principles of the Declaration of Helsinki and was approved by the ethics institutional committee (Protocol IRB#893/2018 for slow running speed dataset and fast running speed dataset, CAR 82/2021 for moderate running speed dataset). Informed consent was obtained from all participants included in the study. All runners were instrumented with two foot-mounted magneto-inertial sensors (MIMUs), which underwent to quality verification [34] and whose sample frequencies were selected in accordance with best practice [35]. All participants performed an initial 10-second standing calibration and were allowed to warm up prior to data collection. Runners were allowed to rest, as needed, between consecutive trials. Results were compared to concurrent stereo-photogrammetric (SP) data, considered the in-lab GS, or concurrent pressure insole data, considered the portable GS. Participant characteristics for all three datasets are described below.

1) SLOW RUNNING SPEED DATASET (8 km/h AND 10 km/h)

Ten recreational runners (5 M, 5F, age: 21±1.3 years, height: 167±7.1 cm, mass: 63±8.6 kg) ran in their native shoes on a treadmill and on a running track at 8 and 10 km/h for 400 m for a total of 4 running trials per speed. Running speed was kept constant by a running pacer. Two MIMUs (mod. MITCH, 221e S.r.l., Italy; 3D accelerometer: range ±16 g; 3D gyroscope: range ±2000 dps; 3D magnetometer: range ±50 Gauss; fs = 100 Hz) were fixed to the instep of each shoe (Fig. 5*a* − *c*) [34]. Instrumented pressure insoles (mod. YETI, 22le Srl, Padua, Italy; sixteen pressure sensors; element area = 310 mm; force threshold = 5 N; fs = 100 Hz) were inserted in the shoes and used as a portable GS to collect temporal parameters [36], [37]. The method implemented to compute reference IC and FC from pressure insole data can be found in Appendix.

2) MODERATE RUNNING SPEED DATASET (14 km/h)

Ten recreational runners (10 M, age: 32.3±9.9 years, height: 172.5±4.3 cm, mass: 69.4±4.9 kg) performed eight 6-minute running trials at 14 km/h on a treadmill wearing different running shoes. Two MIMUs (mod: Opal v2, APDM, Portland, USA; 3D accelerometer: range ±16 g; 3D gyroscope: range ±2000 dps; 3D magnetometer: range ±50 Gauss; fs = 200 Hz) were fixed on the instep of each shoe (Fig. 5*d*) [34]. Eight retro-reflective markers (placed on right and left heels, toes, ankles and each MIMU) were used to collect motion data via SP system (9)-camera Vero system, Vicon, Oxford, UK; fs = 200 Hz) and considered as a GS (Fig. 5*d*). The implemented method to compute reference IC and FC from toe and heel trajectories can be found in Appendix.

3) FAST RUNNING SPEED DATASET (19-30 km/h)

Ten elite runners (8 M, 2F, age: 23.6±3.9 years, height: 175.9±7.4 cm, mass: 67.7±11.4 kg) ran in their native racing spiked shoes along a 50m-straight running track at their maximal speed (average sprint speed between 19 km/h and 30 km/h) for 6 to 12 trials. The first right and left stride for each trial were disregarded because runners started sprinting from a standstill position. Each participant was instrumented with two MIMUs (mod. MITCH, 221e S.r.l., Italy; 3D accelerometer: range ±16 g; 3D gyroscope: range ±2000 dps; 3D magnetometer: range ±50 Gauss; fs = 200 Hz), fixed to the instep of each shoe [34], and two instrumented pressure insoles (mod. YETI, 22le Srl, Padua, Italy, eight pressure sensors; element area = 310 mm; force threshold = 5 N; fs = 200 Hz) (Fig. 5*b* − *c*), considered as a GS [36], [37] (Appendix).

4) DESCRIPTION OF THE RUNNING DATASETS

To describe the running datasets, reference values of the running temporal parameters (i.e., not only stride duration, stance duration, and swing duration, but also step duration,

FIGURE 5. **Experimental setup used in slow running speed dataset (Fig. 5a,c), moderate running speed dataset (Fig. 5d) and fast running speed dataset (Fig. 5b,c). All the setups included two shoe-mounted inertial sensors. In slow and fast running speed datasets a pressure insole was inserted in each shoe and used as a portable gold standard for running temporal parameters. In the moderate running speed dataset (Fig. 5d), trajectories of the retro-reflective markers of the stereo-photogrammetric system were used as a gold standard for the identification of running temporal parameters.**

flight duration, duty factor, and step frequency) were computed from the available GS (i.e., pressure insoles or SP system).

A step was defined by consecutive ICs with the ground of contralateral feet.

Flight duration was computed as the time interval between the FC of a foot and the consecutive IC of the contralateral one.

The duty factor (DF) of a generic *k-th* running gait cycle was defined as the percentage of time in which the foot is in contact with the ground with respect to the entire running cycle:

$$\mathrm{DF}_k = \frac{\mathrm{stance}_k}{\mathrm{stride}_k}\% \tag{7}$$

Step frequency (SF) was estimated as the number of steps performed in a second:

$$\mathrm{SF} = \frac{\#\mathrm{steps}}{\Delta \mathrm{T}_{\mathrm{trial}}} \tag{8}$$

where $\Delta \mathrm{T}_{\mathrm{trial}}$ is the time interval of the running trial in s.

D. METHODOLOGY FOR PERFORMANCE ASSESSMENT

1) VALIDATION OF DTW TEMPLATE-BASED METHOD

A leave-one-subject-out strategy was carried out for the template definition to test the performances of the method in conditions similar to those encountered when a completely new subject is analyzed and avoid subject bias.

For each single subject under analysis, the data from the remaining 29 subjects were considered to select the templates used to analyze that subject. For instance, if the generic subject (n^*) under analysis belonged to the slow dataset, the slow speed templates were defined using the nine remaining subjects of the slow dataset ($\mathbf{T}^*_{\mathrm{S-IC}}$, $\mathbf{T}^*_{\mathrm{S-FC}}$) while the moderate and fast templates were computed using the entire datasets ($\mathbf{T}_{\mathrm{M-IC}}$, $\mathbf{T}_{\mathrm{M-FC}}$, $\mathbf{T}_{\mathrm{F-IC}}$, $\mathbf{T}_{\mathrm{F-FC}}$) (Fig. 6).

Each running gait cycle of subject n^* was analyzed using the $\mathrm{TB}_{\mathrm{DTW}}$ method based on the six templates ($\mathbf{T}^*_{\mathrm{S-IC}}$, $\mathbf{T}_{\mathrm{M-IC}}$, $\mathbf{T}_{\mathrm{F-IC}}$ and $\mathbf{T}^*_{\mathrm{S-FC}}$, $\mathbf{T}_{\mathrm{M-FC}}$, $\mathbf{T}_{\mathrm{F-FC}}$). This procedure was repeated for each of the 30 subjects.

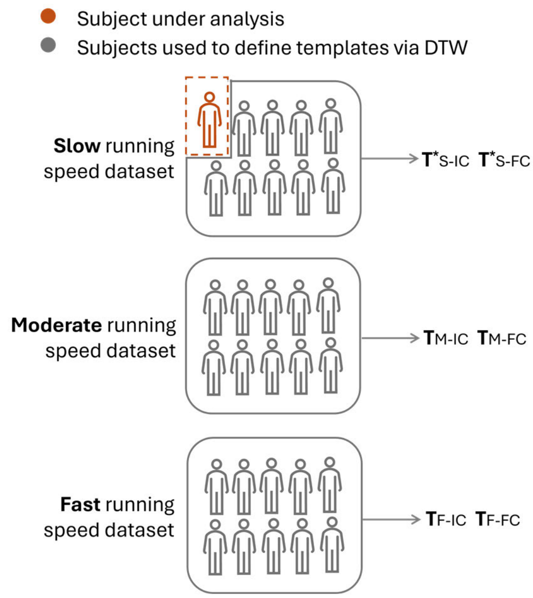

FIGURE 6. **Graphical representation of the template definition for the validation procedure. A generic *n*-th* subject of the slow running speed dataset was analyzed using templates selected from the remaining 29 subjects.**

2) COMPARATIVE ASSESSMENT AND STATISTICAL ANALYSIS

Errors on each estimated parameter P (i.e., IC and FC instant, stride, stance, and swing durations) for each implemented method (M1-M8 and $\mathrm{TB}_{\mathrm{DTW}}$) were computed cycle-by-cycle as:

$$e_{P_{k,n}} = P_{IMU_{k,n}} - P_{GS_{k,n}} \tag{9}$$

where $P_{IMU_{k,n}}$ and $P_{GS_{k,n}}$ are the *k-th* inertial-based and the GS-reference estimate of parameter P of the *n-th* subject, respectively.

Subsequently, for each method and parameter P, mean errors were calculated to obtain a single value me_{P_s} per subject as follows:

$$\mathrm{me}_{P_n} = \frac{\sum_{k=1}^{K_n} e_{P_{k,n}}}{K_n} \tag{10}$$

where me_{P_n} is the mean error of the parameter P of *n-th* subject; K_n the total number of estimates of parameter P for the *n-th* subject. The total number of estimates (i.e., number of running gait cycles) varied across subjects and datasets.

For each speed (slow, moderate, and fast), root mean squared errors (RMSE) of each parameters P were computed across the subjects belonging to that specific dataset as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{n=1}^{\mathrm{N}} \left(\mathrm{me}_{P_n}\right)^2}{\mathrm{N}}} \tag{11}$$

where N is the total number of subjects per dataset (i.e., ten). Furthermore, mean absolute percentage errors (MAE%) of stride, stance, and swing durations for each speed were computed as:

$$\mathrm{MAE\%} = \sum_{n=1}^{\mathrm{N}} \left(\frac{\mathrm{me}_{P_n}}{\bar{P}_{\mathrm{GS}_n}} \times 100\right) \tag{12}$$

where $\bar{P}_{\mathrm{GS}_n}$ is the average reference value of the parameter P of the *n-th* subject calculated from the GS. For statistical analysis purposes, RMSE distributions and MAE% distributions were also computed calculating the overall RMSE and MAE% of each parameter for each subject.

For stride, stance, and swing durations, the intra-class correlation coefficient ICC(2,1) was calculated to assess the reliability and agreement between the parameters estimated with the $\mathrm{TB_{DTW}}$ method and the reference ones across overall speeds [38], [39].

Shapiro –Wilk tests of normality were performed for the error distribution of each parameter, dataset and method to select the most appropriate subsequent statistical analysis. To assess the effect of running speed on running temporal parameters estimation, a one-way analysis of variance (ANOVA) or a Kruskal-Wallis test were performed on normal and non-normal distributions of the obtained error distributions across different speeds, respectively. Pairwise comparisons across speeds were computed on RMSE distributions and MAE% distributions, determining the statistical significance for p-value < 0.05, after a Bonferroni adjustment.

To investigate the output of the template-matching procedure (i.e., which template was selected as the most similar to each running gait cycle under analysis), we counted the number of occurrences that a given running gait cycle was analyzed using a template corresponding to the same speed category.

III. RESULTS

More than 56,000 running gait cycles, including right and left, were analyzed: 32,665 for slow running speed dataset, 22,578 for moderate running speed dataset, and 1,484 for fast running speed dataset. Reference values for the running temporal parameters, collected from the GS, were in accordance with previous studies [40], [41], [42], [43] (Table 2).

The most representative templates for each dataset ($\mathbf{T}_{\mathrm{S-IC}}$, $\mathbf{T}_{\mathrm{M-IC}}$, $\mathbf{T}_{\mathrm{F-IC}}$ and $\mathbf{T}_{\mathrm{S-FC}}$, $\mathbf{T}_{\mathrm{M-FC}}$, $\mathbf{T}_{\mathrm{F-FC}}$) were selected from a running gait cycle of a trial at 10 km/h for the slow dataset, from a trial at 14 km/h for the moderate dataset, and from trial with average speed equal to 26 km/h for the fast dataset.

TABLE 2. Reference values for running temporal parameters provided by the gold standard (pressure insoles or SP system).

	Slow dataset (constant speed 8, 10 km/h)	Moderate dataset (constant speed 14 km/h)	Fast dataset (averaged speed 19-30 km/h)
	Mean ± std	Mean ± std	Mean ± std
Stride (ms)	730 ± 33	690 ± 28	575 ± 50
Stance (ms)	320 ± 27	220 ± 14	170 ± 14
Swing (ms)	420 ± 30	465 ± 31	405 ± 46
Flight (ms)	60 ± 26	120 ± 10	105 ± 11
Step (ms)	370 ± 11	340 ± 7	275 ± 17
DF (%)	43.3 ± 3.2	32.3 ± 2.5	30.8 ± 2.6
SF (#step/s)	2.7 ± 0.1	2.9 ± 0.1	3.8 ± 0.3

SP = stereo-photogrammetric; DF = duty factor; SF = step frequency.
Values are reported considering the temporal resolution of the gold standards (10 ms for slow dataset and 5 ms for moderate and fast datasets).

The comparative assessment showed that for all methods (M1-M8), except $\mathrm{TB_{DTW}}$, errors were significantly influenced by the running speed (Table 3).

TABLE 3. Effect of running speed on the error distributions of running temporal parameters for all the implemented methods.

Method	Stride	Stance	Swing
	p -value	p-value	p-value
M1	**<0.001 ***	**<0.001 ***	**<0.001 ***
M2	**0.001 ***	**<0.001 ***	**<0.001 ***
M3	**<0.001 ***	**<0.001 ***	**<0.001 ***
M4	**<0.001 ***	**<0.001 ***	**<0.001 ***
M5	**<0.001 ***	**<0.001 ***	**<0.001 ***
M6	**<0.001 ***	**<0.001 ***	**<0.001 ***
M7	**<0.001 ***	**0.006 ***	**0.005 ***
M8	**<0.001 ***	**0.032 ***	**0.022 ***
$\mathrm{TB_{DTW}}$	0.156	0.150	0.155

$\mathrm{TB_{DTW}}$ = DTW template-based method.
*Significant (p-value < 0.05) effect is highlighted in bold.

The RMSE of IC and FC identifications for all methods is reported in Table 4. Boxplots of the error distributions across all methods and speeds are reported in Fig. 7.

To further explore the results of the $\mathrm{TB_{DTW}}$ method, RMSE and MAE% values of each running temporal event and parameter are reported in Table 5. Values for ICC(2,1) across overall running speeds were equal to 0.91, 0.80, and 0.75 for stride, stance, and swing duration, respectively.

The percentages of running gait cycles analyzed using a template belonging to the same dataset are reported in Fig. 8.

IV. DISCUSSION

In this study, eight well-established foot-mounted inertial-based methods for IC and FC estimation during running were implemented and their validity was analyzed [5], [6], [11], [12], [13], [15], [18], [20].

TABLE 4. Root mean squared errors (RMSE) on initial contact (IC) and final contact (FC) estimation for all the implemented methods.

Method	Parameter	RMSE (ms) 8, 10 km/h	14 km/h	19-30 km/h	All speeds
M1	IC	20	25	50	35
	FC	135	60	80	90
M2	IC	**15**	25	30	25
	FC	**20**	70	25	40
M3	IC	35	50	95	60
	FC	65	50	65	60
M4	IC	20	**25**	60	35
	FC	85	**20**	45	50
M5	IC	90	80	40	70
	FC	60	35	30	40
M6	IC	35	55	35	40
	FC	40	40	25	35
M7	IC	20	35	**20**	**25**
	FC	20	50	**15**	**30**
M8	IC	20	35	25	25
	FC	20	25	120	55
TB_{DTW}	IC	**10**	**15**	**15**	**15**
	FC	**20**	**20**	**25**	**20**

TB_{DTW} = DTW template-based method.
For each speed, the two lowest errors are highlighted in bold.

TABLE 5. Results of the estimation of running temporal parameters using the TB_{DTW} method.

Dataset	Mean metric	Stride (ms)	Stance (ms)	Swing (ms)
8, 10 km/h	*RMSE* *(MAE%)*	<10 (<1 ± <1) [b]	30 (7 ± 6) [b]	30 (6 ± 4)
14 km/h	*RMSE* *(MAE%)*	<5 (<1 ± <1) [c]	20 (7 ± 7) [c]	20 (3 ± 3)
19-30 km/h	*RMSE* *(MAE%)*	<5 (<1 ± <1) [b,c]	30 (19 ± 10) [b,c]	30 (6 ± 3)

[a] Significant difference (p-value < 0.05) between datasets at slow speed and at moderate speed;
[b] significant difference (p-value < 0.05) between datasets at slow speed and at fast speed;
[c] significant difference (p-value < 0.05) between datasets at moderate speed and at fast speed.

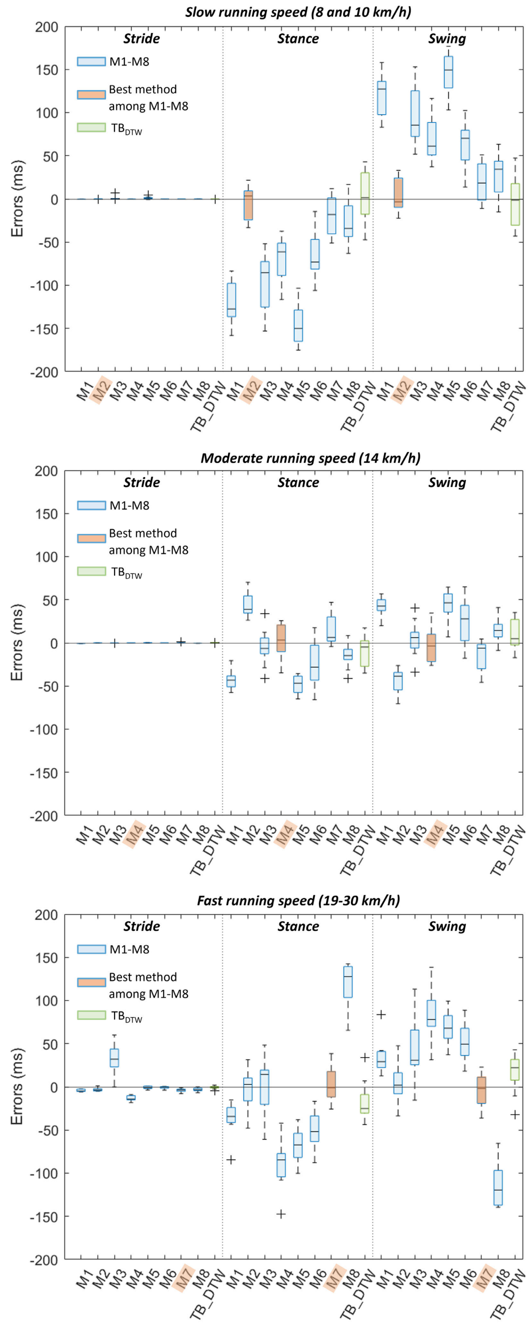

FIGURE 7. Boxplots of the error distributions for the estimation of stride, stance, and swing durations during slow, moderate, and fast running speeds obtained with different methods from the literature M1-M8 (in blue) and the proposed TB_{DTW} method (in green). To facilitate the readability of the plots, boxplots of the methods from the literature showing the best results at each running speed are highlighted in orange: M2 for slow running speed, M4 for moderate running speed, and M7 for fast running speed.

In addition, an original method based on template-matching using DTW algorithm was proposed and compared.

Most of the inertial-based methods from the literature identify IC and FC based on speed-specific signal features and have been validated on specific running speeds [11], [12], [13], [15], [18], [20]. Conversely, the proposed TB_{DTW} method was designed to be robust to speed changes, through stretching signal morphology of three speed-specific templates (i.e., slow speed, moderate speed, and fast speed). To the authors' knowledge, this is the first study implementing a DTW-based method for the estimation of running temporal parameters from jogging to sprinting.

Performances of the selected methods were tested on three datasets (over 56,000 running cycles) including slow running speed (8 km/h and 10 km/h), moderate running speed (14 km/h), and fast running speed (sprinting at average speed equal to 19-30 km/h), thus encompassing a wide range of running speeds (∼22 km/h). The speed range tested in this study extended previous analyses for assessing the effect of

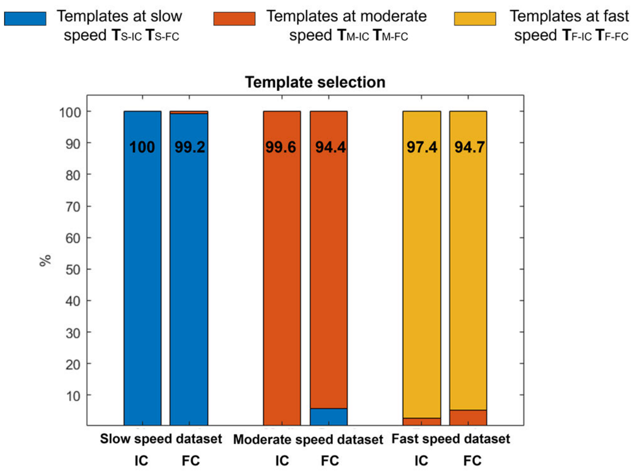

FIGURE 8. Percentage of template selection among available templates (for slow running speed, moderate running speed, and fast running speed) for the identification of initial contact (IC) and final contact (FC) for each dataset.

running speed (i.e., range of ~10 km/h, including speeds from ~ 10 km/h to ~ 20 km/h, in [6], and range of ~18 km/h, from 9 km/h to 27 km/h, in [22]).

Methods performances were investigated both on treadmill running, using the SP system as reference, and overground running, using pressure insoles as reference. The use of pressure insoles enabled to provide reference temporal parameters along 50-m and 400-m paths on running track, thus increasing the number of detected strides on track with respect to traditional GS used in outdoor settings such as photocell system [13], [20] and high-speed cameras [4], which limit the analysis to a restricted number of strides.

The estimation of stride, stance, and swing durations in all the tested methods from the literature (M1-M8) was significantly affected by running speed (p-value from <0.001 to 0.032). This was in accordance with previous literature assessing the speed-dependance of inertial-based methods based on peak detection or thresholding across running speeds [6], [22]. The stride duration was accurately estimated by all the methods, except for M3. Conversely, for stance and swing parameters, we found a great variability in errors at different running speeds using M1-M8. In general, results for stance and swing durations were more accurate at moderate speed (14 km/h) (median error always below ~ |50| ms) than at slow speed (8 km/h and 10 km/h) and fast speed (19-30 km/h) (median errors up to ~ |160| ms).

The best performing methods from the literature were different depending on the tested speed: M2 for slow running speed ($RMSE_{IC} = 15$ ms, $RMSE_{FC} = 20$ ms), M4 for moderate running speed ($RMSE_{IC} = 25$ ms, $RMSE_{FC} = 20$ ms), and M7 for fast running speed ($RMSE_{IC} = 20$ ms, $RMSE_{FC} = 15$ ms). Thus, these methods (M2, M4, and M7) could be appropriate for analyzing running at specific and a priori known speeds.

Conversely, the performance of the proposed TB_{DTW} method in estimating stride, stance, and swing was independent of speed (p-value > 0.150). Overall, the TB_{DTW} method showed higher or comparable accuracy with respect to the best methods from the literature at all speeds ($RMSE_{IC}$ = 10-15 ms, $RMSE_{FC}$ = 20-25 ms across speeds). This aspect makes the method suitable for a very wide range of running speeds, fostering its applicability in different sports characterized by changes in speed.

The TB_{DTW} method provided good to excellent reliability (ICC(2,1) for stride, stance, and swing durations between 0.75 and 0.91) and accurate performance across different running speeds (RMSE for stride duration always below GS resolutions, i.e. 10 ms or 5 ms; RMSE for stance and swing durations always below or equal to 30 ms). The RMSE values for stride duration at different speeds were statistically different (p-value < 0.05) but negligible (RMSE below one sample). For stance duration, we did not find statistical differences in RMSE (p-value > 0.05) but rather in percentage errors (p-value < 0.05). This can be explained by the very different nominal durations of stance phases at different running speeds (from 170 ms to 320 ms). Errors in estimating swing duration were not affected by speed (p-value > 0.05).

The percentages of running gait cycles analyzed selecting a template belonging to the same dataset were extremely high (between 94% and 99%), irrespective of the subject's anthropometric characteristics and running conditions (indoor/outdoor; constant/non constant running speed; footwear). This finding suggests that the use of templates at three different speeds (slow, moderate, and fast) is reasonable and represents a good trade-off choice from a computational perspective for running analysis from 8 km/h to sprinting.

A point of strength of the proposed TB_{DTW} method is that data were pre-segmented between consecutive mid-swing instants, conversely to previous DTW-based approaches specifically conceived for gait analysis, which segmented stride/stance intervals using templates' IC and FC instants [29], [30]. This led to both precision and recall in IC/FC detection in running equal to 100%.

Among machine learning approaches proposed in the literature for the estimation of running temporal parameters, recently a LSTM method was tested across different speeds (8-19 km/h) [17]. This study reported RMSE values on IC and FC ranging between 16-39 ms and 14-59 ms, respectively. Hence the performance of the LSTM method was comparable to M1-M8, but worse than the TB_{DTW} method (see Table 4).

The validation of the TB_{DTW} method must be considered in the light of some limitations. First, the TB_{DTW} method was implemented using three speed-dependent templates derived from as many datasets which were also used for the testing. Since the slow running dataset included two running speeds only (8 and 10 km/h) and the moderate running speed dataset only a specific speed (14 km/h), it can be speculated that using a template defined from the same speed, or for a speed very close to that one under analysis, would facilitate the matching procedure. However, this was not the case for the fast running speed dataset, which included stride-by-stride speed ranging from ~12 to 32 km/h (the subjects started from a standstill, but the first two running cycles were discarded), and for which the proposed method was still very effective. For the FC identification in the fast speed dataset, the fast running template was chosen for ~ 95% of the running cycles, while for the remaining ~ 5% the matching was performed using the moderate running template (see Fig. 8). Future research should investigate in depth the relation between the stride speed of the running gait cycle under analysis and the speed of the selected template. This additional investigation could also be associated with an error analysis of the impact of reducing or increasing the number of speed-dependent templates.

Furthermore, although no specific investigations were conducted, preliminary analyses did not reveal evident differences in TB_{DTW} performance when varying running conditions (i.e., treadmill and overground), surfaces (i.e., treadmill belts and synthetic tracks), and foot strike types (i.e., rearfoot, midfoot, forefoot), suggesting that the method is promising for the analysis of various running patterns. However, its application to the analysis of irregular running patterns (e.g., trail running, obstacle racing) would require further investigations and potentially the adoption of specific templates.

The performance of TB_{DTW} method was computationally efficient (the computational cost required to analyze a single running gait cycle was ~10 ms), although an entire segmented running gait cycle is needed to extract the temporal parameters via template-matching, which limits real-time applications.

The implemented MATLAB code related to the TB_{DTW} method and the relevant template library are made available at https://github.com/H-MOVE-LAB/run_imu.git. The sample frequency of the templates is 100 Hz (slow running dataset) or 200 Hz (moderate and fast running dataset), however they can be also used to analyze data recorded at different sampling frequencies after a convenient resampling. Data preprocessing is suggested to avoid excessive template stretching due to a great disparity in the number of samples between the template and the running gait cycle under analysis (e.g., 100 Hz *vs* 500 Hz). Moreover, caution should be paid when using the low-frequency templates provided in the open-source repository (fs = 100-200 Hz) to analyze high-frequency data (fs ≥ 800 Hz), as in such cases, it would be preferable to use high-frequency templates.

V. CONCLUSION

Out of the nine methods tested, the proposed DTW-based template matching method was least affected by speed changes and the most accurate across different running speeds with errors below 0.1% in stride estimation, between 7%-19% in stance estimation, and between 3%-6% in swing estimation.

The DTW-based template matching method represented an effective and valid solution for an inertial-based running analysis at any speed between 8 km/h and 30 km/h, which encompasses typical running speeds of recreational to elite runners. This aspect makes it a promising solution to analyze running for steady state activities as well as in sports that have frequent fluctuations in speed such as soccer, football, or baseball.

APPENDIX

ESTIMATION OF INITIAL AND FINAL CONTACT INSTANTS FROM GOLD STANDARDS

The methods for the estimation of reference IC and FC are described below.

A. ESTIMATION OF INITIAL AND FINAL CONTACT FROM PRESSURE INSOLES

Instrumented pressure insoles were demonstrated to be an effective portable GS for the estimation of gait events during walking [36], [37] and running up to sprinting [44], [45], [46]. To exclude any potentially low-quality pressure data, a quality check on the pressure insole data was preliminarily carried out. The first derivative of pressure insole signals revealed sharp rising and falling edges in correspondence to the IC and FC instants, due to a fast pressure sensor activation and deactivation at foot strike and off, respectively [36]. Then, the activation or deactivation of a cluster of at least two sensing elements, with a maximum discrepancy of 0.1 s, defined the research windows for IC and FC instants. An IC was defined as the last rising edge instant of the first sequentially activated cluster, while an FC was identified as the first falling edge instant of the last sequentially deactivated cluster [46] (Fig. 9).

This GS method was used for slow and fast running speed datasets.

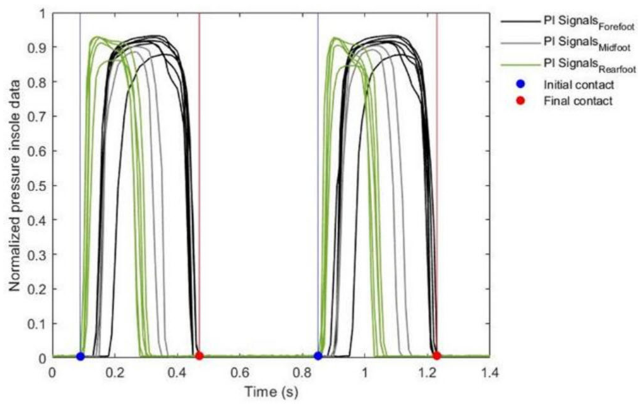

FIGURE 9. Initial and final contact instants estimated with pressure insole (PI) data at 8 km/h.

B. ESTIMATION OF INITIAL AND FINAL CONTACT FROM STEREO-PHOTOGRAMMETRIC SYSTEM

Trajectories of retroreflective markers placed on heels and toes were used to detect reference ICs and FCs [47], [48], [49] (Fig. 5*d*). An IC was defined in correspondence of the first value of the vertical displacement of the heel marker lower than a parametric threshold, based on the minimum value of the heel vertical displacement within the current stride incremented by 3 cm. A FC was identified as the instant in which the rising profile of the vertical displacement of the toe marker exceeds a parametric threshold set to twice the minimum value of the toe vertical displacement within the current stride.

This GS method was used for the moderate running speed dataset.

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